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# An Exploratory Sentiment and Facial Expressions Analysis of Data from Photo-sharing on Social Media: The Case of Football Violence

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**Abstract**
In this article we propose the possibility to increase the level of security during football matches due to analysis of data that are placed on the social networks of these events visitors. We considered different ways to recognize emotions from photographs to trace the changes in the level of emotions in the photos depending on whether these pictures were taken during the game with fights in the stands or during normal games. We tested this assumption and our hypothesis has been partially confirmed. The software solution for emotion recognition from Microsoft Oxford showed that the level of emotional anger is noticeably higher in the photographs taken during the match with fights. In addition, other curious results were obtained, including an analysis of the key of the comments left by events visitors' photos.

*Keywords:* sentiment analysis, facial expression recognition, social media, football violence, data analysis

## 1 Introduction

According to research of Statistic Brain Research Institute, football is the most popular sport in the world. About 3.5 billion people follow this type of competition[1]. Each week football matches are held at various levels around the world. The average attendance at football games is relatively high compared to other sporting events – for example, around 40 thousand spectators came to every Bundesliga game in Germany in 2015 [2]. In the United States, during the same period, the audience at football matches exceeded 20 thousand visitors [3]. In terms of match attendance, Russia has one of the lowest numbers in Europe, but the number of spectators at the events of the Russian Major League exceeded 10 thousand people [2].

Football culture and violence have been inseparable since the introduction of professional football in England in the late 19th century [4]. Constant skirmishes between fans occur both outside the stadium


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and in the stands. Violent clashes during a match only contribute to the increasing tensions between rival fans. In the entire history of football in the world there have been many notable incidents are further the most important ones described. On November 6, 1955 during the match “Napoli” - “Bologna” in Naples, there was unrest in the stands, injuring 152 people [5]. October 31, 1976 in Cameroon was marked by fights among the fans during a match of the local national team against Congo, which resulted in the deaths of two people [6].

Similar events continue to occur today. The biggest tragedy in recent years took place in Egypt. The match between the “Al-Masri” and “Al-Ahly” clubs, in which the hosts triumphed with a score of 3:1, ended in a massive attack on a group of spectators supporting the visiting team [7].

To avoid such cases, the authorities develop special regulations, imposing more control over the fans or increasing the number of police officers in the stands. However, the quantity of law enforcers present during the event has very little to do with the accurate prediction of potential confrontations between the fans or the infliction of material damage, since the intentions of football fans to start a clash are hidden from police.

This study has been carried out in an attempt to pursue the ultimate goal – assist the anticipation and timely prevention of future fights in stadium stands. Moreover, this is closely related to the market of mobile devices and social networks.

Today there are around 2.6 billion smart phones in use worldwide [8]. Analysts predict that by 2020 the number of devices will grow up to 6.1 billion [8]. Along with the increasing popularity and availability of smartphones, the social media market continues to evolve, too. As of August 2015, there were more than 2.2 billion active social network users in the world [9]. Today, social networks are not just a platform for interaction, communication, and cooperation. Services like Facebook, Twitter, Instagram also facilitate the collective participatory formation of an aggregate reflective view of the most important events of the present as well as an outlook to the past and future. Growth of the market of mobile devices and social networks is motivating the use of these funds for the solution of contemporary problems of society.

These facts lead us to assume that conclusions about the prevailing mood as a proxy for violent intentions during a soccer match can be drawn from the assessment of the “tone” of the facial expressions found on the photos taken by spectators and comments related to them. In this research, we gave preference to Instagram as the source of both textual and visual data. This social network has 400 million monthly active users [10], is developing dynamically (its growth doubled in 2015), is mainly accessed from smart phones, stores user geo-location data linked to entries and is widely distributed in Europe, North and South America [11]. Instagram is a convenient source of data – it provides researchers not just visual data (photos and short videos), but text (comments to posts). And last but not least, Instagram provides developers with a convenient API to retrieve data from servers.

# 2 Related Works

Sentiment analysis is a part of appraisal theory, which is focused on automatically identifying text topics or semantic which influence on real life action. Many studies focus on the semantic analyses to understand “positive”, “negative” or “neutral” sentiment polarity and ones weights [12]. Sentiment analysis in online communication between people successfully predicts product consumption preferences and the trust among friends. The experiment results show that informal and short posts can predict preferences without any information history about preferences before [13].

Methods of emotion recognition are divided into three categories, based on the methods of face recognition: template-based methods (associated with holistic approaches to face recognition), feature-based methods (for the analytic-following approach to recognition of faces), and hybrid ones [17].

The Active Appearance Model (AAM), Labeled Graph Method (LGM), Point Distribution Model (PDM), Random Block Eigenvectors (RBE) belong to the first category, while Facial Characteristics

Point Method, Dual-View Point-Based Method belong to the second. Fiducial Grid & Gabor Wavelets, Potential Net belong to the third [17].

AAM was first used by Edwards, Cootes, and Taylor in the context of the analysis of individuals in the third International Conference of Pattern Recognition and gestures. The algorithm is based on optimizing the differences between the current image and the original sample. This method allows to achieve an accuracy of 88% [18].

Random Block Eigenvector Method allows one to get rid of redundant information in the study of facial features. The system selects only the necessary parts of the projection, which allows for an 86% algorithm efficiency[19].

Dual-View Point-Based Method uses a combination of frontal and side view of the same person, to achieve a successful outcome in 86% [20].

Fiducial Grid & Gabor Wavelets combination of methods possible to combine the advantages of two different approaches to get rid of the sensitivity of the method of Gabor Wavelets and get a successful result in 82% [21].

In this section, we describe the currently known methods of recognition of emotions from photographs. These methods are widely used in commercial products with various degrees of success. Since these methods demonstrate a similar level of effectiveness in performing standard tasks, we relied on the comparison of the existing commercial solutions (presented in Section 3 of the paper) when choosing specific technologies to be applied to the study.

# 3 Study

## 3.1 Dataset

The choice of cases to be considered in this research has been limited to those events that occurred in 2015 primarily due to the two-fold increase in Instagram users that year [10]. Based on the information obtained from news websites, a total of eight matches, characterized by the incidence of fights in the stands, have been chosen. In contrast, we have selected home games of the same teams, which took place in the 2015 and during which there were no fights in the stands. It is worth noting that though a lot more than eight games with fights in the stands have been found, the majority of them have been excluded from the investigation as lacking sufficient number of relevant photos uploaded to Instagram. Moreover, such factors as the features of the stadiums, results of the games, and the history of prior confrontation between the fans of different teams has not been taken into consideration in this study.

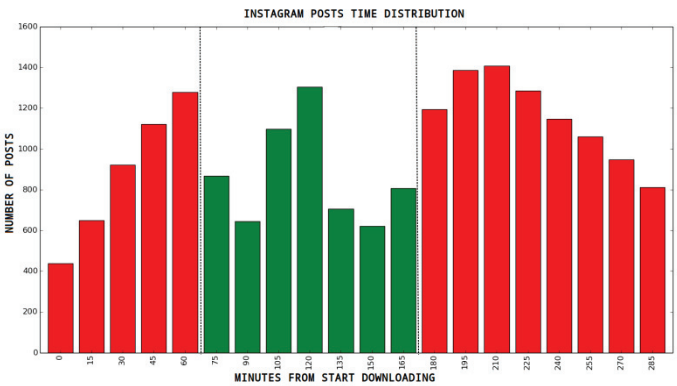


**Figure 1:** Instagram posts time distribution

For each case under investigation, a set of pictures containing geo-location marks and uploaded to Instagram in the course of the game was extracted. With the help of Google Maps service [22], the coordinates of the stadium were acquired and transferred as input data for the media data search function of Instagram API. It was also applied to the start time of the match, and the time interval for searching photos was equal to five hours. These photos have been transferred to the input for each of the services we have chosen to recognize emotions.

Each of the used services returns the results of the processing of each of the detected faces in a photo. Instagram photo comments were used as initial data of the discourse analysis of social unrest prediction. Those photos were the same as in the photo analyses. For Instagram comments, collecting API requests with the photo id was applied. As output, 1248 text data with photo “tags” and “comments” were collected.

## 3.2 Text Sentiment Analysis

In this study, semantic analysis of photo comments was applied with the hypothesis that the higher level of “negative” posts correlate with the social unrest in football matches. Firstly, all texts for creating the initial form were lemmatized with the help of open software “mystem.exe” from “Yandex”[21]. Due to its nature, the textual content (predominantly user-generated) that is found on social network sites has many specific words and figures of speech, which complicate the process of the model training. [22] For reducing error in training comments sentiment, Support Vector Machines (SVM) models were applied on the Russian social network sites dictionary.

## 3.3 Face Emotion Analysis

Currently technology recognition cease to be unattainable, and they are increasingly found in the implementation of commercial products.

FaceReader by Noldus Information Technology [23] is among the solutions, that are based on template-based methods.. Development of Dutch scientists can recognize "happy," "sad," "angry," "surprised", "afraid", "dissatisfied" and "neutral" facial expressions. FaceReader is also able to identify age, gender, and ethnicity from a face in a photo. The average percentage of emotion recognition is 89% [23]. In addition, the market is represented by the development of the company Visual Recognition - GladOrSad [24]. Emotion recognition system creates 3D-model of the person with the identification of 12 key areas, such as the corners of his eyes and the corners of the mouth. The program is able to allocate six emotions: anger, sadness, fear, surprise, disgust and happiness, as well as the seventh - their mix [24]. There is also Luxand Face Recognition system [25]. The software product of the American company Luxand can automatically determine the sex of the subject based on the image or video. Developers claim success of identification as 93% in the image processing, and 97% - in the video. In addition, the program is capable of measuring "happiness level". [25]. And the newest one is the Microsoft Oxford project (Figure 2) [26]. Introduced in November 2015, technology, relying on machine learning algorithms, can recognize eight emotions (anger, contempt, disgust, fear, happiness, neutral, sadness, surprise). Developers allowed free use of the the API of the service, which made it widespread [26].


**Figure 2:** Example of Facial emotion recognition by Microsoft Emotion API

The next group of services is feature-based methods. SkyBiometry system is able to determine the level of presence in the top six photos of emotions and a neutral mood [27]. Affective Computing Research Group System [28] is based on Gabor Wavelets and is able to assess the six emotions (anger, sadness, fear, surprise, disgust and happiness) [28] Face++ is designed primarily for identification and verification of persons. In addition, Face ++ is able to assess the gender, age and level of human joy.

Developers marked the success level of the application on 87%. The system is based on the structure of deep neural network [29] And an application by Sightcorp – InSight - can track the tiniest movements of the facial muscles on the face of the user and recognize six emotions. In addition, the system can uniquely track eye movement in order to understand the laws of the user's attention and visual stimuli that captures their interest. The developers say that the accuracy of the application is 93.2% [30].

Based on our research, we have chosen to operate two services – Microsoft Oxford Project and InSight by SightCorp. Our selection is based on usability services through web-API, the limited possibilities of free use, a high level of recognition of the claimed emotions and appropriate for us to limit requests to the server.

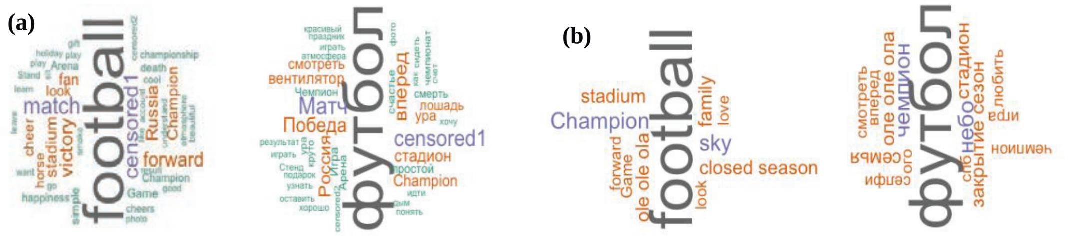


**Figure 3:** (a) Comments word clouds in matches with fight (EN/RU);
(b) Comments word clouds in matches without fight (EN/RU)

# 4 Results

Two word clouds (Figure 3) were created for visual data representation. These word clouds show the most frequently used words (the size and color depends on the word frequency). There are more offensive language words, threats and people associate the fans in games with fights (as seen in Figure 3a). Moreover, in those events where fights did not occur, there were less negative words and more words with high positive scores such as love, family etc. (in Figure 3b).

We have analyzed the collected photos with two services and receive results displayed in Table 2 and Table 3.

| Service | Anger /100 | Contempt /100 | Disgust /100 | Fear /100 | Happiness /100 | Neutral /100 | Sadness /100 | Surprise /100 |
|---|---|---|---|---|---|---|---|---|
| MS | 0.59 | 1.08 | 0.23 | 0.15 | 67.06 | 28.09 | 0.92 | 1.87 |
| SightCorp | 11.17 | - | 11.55 | 6.86 | 36.59 | - | 13.91 | 3.74 |

**Table 1:** Emotions scores for normal matches

| Service | Anger /100 | Contempt /100 | Disgust /100 | Fear /100 | Happiness /100 | Neutral/ 100 | Sadness /100 | Surprise /100 |
|---|---|---|---|---|---|---|---|---|
| MS | 2.89 | 1.19 | 0.63 | 0.19 | 64.02 | 28.52 | 0.95 | 1.60 |
| SightCorp | 10.45 | - | 12.13 | 7.84 | 35.28 | - | 13.99 | 4.53 |

**Table 2:** Emotions scores for fight matches

Table 2 includes the results of the processing of photos collected during the matches held in normal conditions, with no fights. Table 3 contains the results of the data collected during the game with fights in the stands.

After examining the output of the two emotion recognition services, we found that all of them have recorded the prevalence of positive or neutral emotions over negative during all considered matches. In addition, SightCorp system didn't detect elevated levels of any emotion during games with fights. However, the exploring results of Microsoft Oxford Project showed that the average of anger emotions in photos taken during matches with fights, more than in the normal ones in 2.4 times. The distributions of anger is shown if Fig. 4. Except the peaks at zero, the left distribution has peak at the high level of emotion scores.

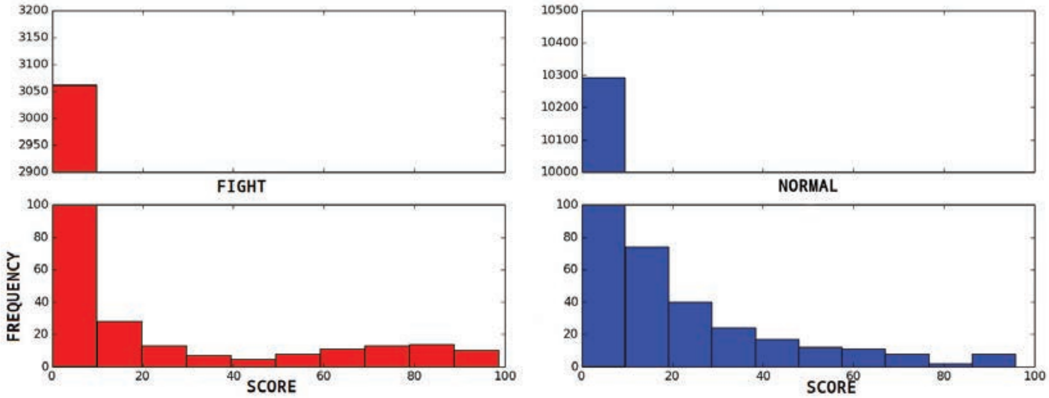


**Figure 4:** Distribution of anger (by MS Oxford)

We suppose that these results can be interpreted as a beginning of a confirmation of the hypothesis that the level of negative emotions in the photos during matches with episodes of violence in the stands will be higher than in the photos taken during normal games.

# 5 Match Classifier Development

After exploring the results of the emotion analysis, we began to develop a classifier for further construction of the system of detection of fights in the stands during the match. For example in the Figure 5 it can be seen that mean level of anger of fight matches is noticeably higher than in normal matches.

For each match we had the following information: data from Instagram (the number of photos, videos, likes, comments, the Instagram users who tagged in the photo), the two sets of emotions values (by MS Oxford Project and SightCorp), and information about filled the stands during the match. Features for classification were selected by function "SelectKBest" from Python library scikit-learn, which removes all but the k highest scoring features.

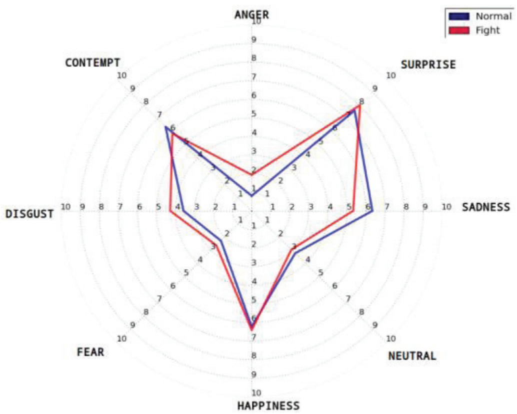


**Figure 5:** Emotions radar-plot (by MS Oxford)

As classifiers were used Naive Bayes classifier, K-nearest neighbors classifier, Decision tree classifier and Extra-tree classifier. The classifiers results verification was done with cross-validation, which was implemented in scikit-learn library. In addition, permutation test was used for testing classifiers. Series of experiments were performed for the variate of the number of using features (Table 4).

| Features # | Naive Bayes | Perm | KNN(k=5) | Perm | Decision tree | Perm | Extra-tree | Perm |
|---|---|---|---|---|---|---|---|---|
| 3 | 85.5 | 76.0 | 77.4 | 80.4 | 86.0 | 74.4 | 88.9 | 74.6 |
| 4 | 81.5 | 75.6 | 77.2 | 79.6 | 85.5 | 80.1 | 87.7 | 76.8 |
| 5 | 77.6 | 77.8 | 79.5 | 79.4 | 84.6 | 78.7 | 84.1 | 77.1 |
| 6 | 77.7 | 76.3 | 79.6 | 79.4 | 83.7 | 74.9 | 83.0 | 78.0 |
| 7 | 77.4 | 71.3 | 79.9 | 79.5 | 82.7 | 75.3 | 82.8 | 78.9 |
| 8 | 79.8 | 70.5 | 75.7 | 79.5 | 81.6 | 74.5 | 82.9 | 78.0 |
| 9 | 78.5 | 69.6 | 75.8 | 79.6 | 81.3 | 73.2 | 83.3 | 78.0 |
| 10 | 79.0 | 70.6 | 79.9 | 79.7 | 80.8 | 73.9 | 82.4 | 77.6 |

**Table 4:** Result of classifiers tests

In addition, after extended feature selection we have chosen the five features: ratio of the number of photos with level of “anger” higher than 70 (by MS Oxford Project evaluation), average of likes, max “surprise” level (by SightCorp evaluation), median “fear” level (by SightCorp evaluation), ratio of the number of photos with level of “fear” higher than 50 (by MS Oxford Project evaluation), see Table 5.

| | Naive Bayes | Perm. | KNN | Perm. | Decision tree | Perm. | Extra-tree | Perm. |
|---|---|---|---|---|---|---|---|---|
| accuracy | 83.3 | 48.3 | 70.5 | 79.5 | 83.6 | 77.2 | 82.5 | 75.3 |
| p-value | 0.0232 | | 0.9767 | | 0.0930 | | 0.0465 | |

**Table 5:** Result for classification with specific features

The p-value is then given by the percentage of runs for which the score obtained is greater than the classification score obtained in the first place.

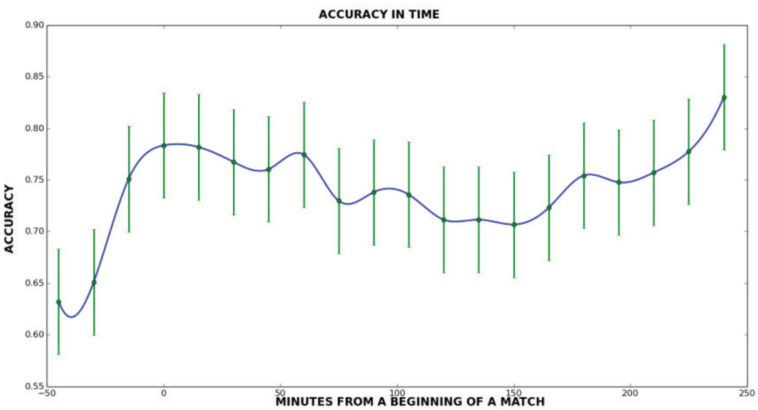


**Figure 6:** Dependency between accuracy and time from the beginning of a match

We got a result, which based on analysis of only five features – four different emotions level and likes value from Instagram data – by Naive Bayes Classifier. We did not use sentiment analysis of text from comments. The dependence between accuracy of classifier and time is shown in Fig 6. In addition to test the classifier, we used permutation tests. Tags “fight” for the matches set were shuffled before running the classifier randomly. During this test, the accuracy was 48.3. This result is not good enough to confirm our hypothesis. We hope the further development of methods and increase of data allow developing this area.

# 6 Discussion & Conclusion

Our study was the beginning on the way of the confirmation hypothesis about the dependence of the level of emotion in photos, which were taken during the match, the availability of forms of violence in the stands during the match.

To fully confirm this hypothesis it is necessary to consider the set accompanying factors such as the history of the opposition contenders, the gender composition of the spectators in the stands, the availability of alcohol, the scoring, and the general mood of society.

However, the confirmation of the hypothesis opens the possibility of implementing a system of monitoring the state of the fans in real time for prevent episodes of violence in the stands. In addition, such system can be used not just during sporting events, but also during concerts, rallies and other public events. In our study we could not get direct confirmation of our hypothesis. We believe that to successfully perform this task, it is necessary to have more data, diverse data sources, and take into account more factors that affect the final outcome.

As one of the measures to improve the accuracy of predictions, we see the possibility of video processing, which are made by visitors during matches or obtained from other sources. This kind of data is different from images and it needs different methods of processing. To accomplish this, the conduction of additional study of existing methods and software solutions in the field of dynamic emotion analysis should be done.

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